AUTHORS:
John W. Hargrove[1]
Pietro Landi[2,3]
Willie Brink[2]

AFFILIATIONS:
[1]South African Centre for Epidemiological Modelling and Analysis (SACEMA), Stellenbosch University, Stellenbosch, South Africa
[2]Department of Mathematical Sciences, Stellenbosch University, Stellenbosch, South Africa
[3]National Institute for Theoretical and Computational Sciences (NITheCS), Stellenbosch, South Africa

CORRESPONDENCE TO:
John Hargrove

EMAIL:
jhargrove@sun.ac.za

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Written on the wings: Morphometrics, mortality and more

Significance:

We describe the development of a machine learning algorithm that automates the location of landmarks on insect wings, thereby allowing rapid calculation of wing size and shape. While the method was developed using tsetse wings, it is readily applicable to all wings and other structures. The method will be useful in determining wing size and shape and how these measures change with meteorological variables and between populations. Such changes can allow identification of isolated pest populations, which can be earmarked for elimination, or of threatened species in need of conservation. They could also provide measures of rates of climate change.

Evolution is written on the wings of butterflies.
Charles Darwin

Dylan Geldenhuys, the lead author and chief protagonist of a 2023 paper[1] describing a machine learning algorithm, allowing semi-automatic detection of landmarks on insect wings, was a master's student making his first foray into the world of scientific research. What was more impressive was that the paper went far beyond the requirement for such a thesis – making a serious contribution to the rapidly burgeoning field of morphometrics.

Morphometrics involves the *quantification and statistical analysis of form*[2,3] and the discipline has applications in multiple fields, including engineering and the physical, biological and medical sciences. In the world of entomology, morphometrics has been used to characterise the shape of insect wings – and it was this feature that caught our attention. It had been suggested that differences in the shape of the wings of populations of tsetse (*Glossina* spp.) – vectors of human and livestock trypanosomiasis – could indicate genetic isolation of particular populations, marking such populations as candidates for elimination, without fear of reinvasion from neighbouring populations.[4,5] The studies involved locating 11 key intersections, between veins, on the wings of individual flies (Figure 1). The relative positions of these so-called *landmarks* define the *shape* of a given wing.

What concerned us was that no studies had been conducted to assess the natural variation in wing shape, with time and season. Such temporal variation, within a single population, might swamp differences between geographically separated populations and thereby prejudice, or even vitiate, any conclusion that neighbouring populations were indeed genetically isolated. A review of the literature immediately revealed, however, that the samples analysed to date were so small – generally involving fewer than 200 flies – that they could not support a meaningful statistical analysis of temporal variation.

We were able to address this shortcoming because we had access to a collection of over 200 000 pairs of wings, collected over 11 years, at Rekomitjie Research Station, in the Zambezi Valley of Zimbabwe.[6] Whereas earlier workers were able to locate landmarks using a manual procedure, this approach was impractical in our case – given the very much larger numbers of wings we had available. What we needed was an artificial intelligence type of approach, where a computer could learn to recognise the wing of a tsetse and, thereby, to zero in on the landmarks and position them automatically. Which was where Dylan Geldenhuys came into the picture – although not before several other workers had made contributions, without actually delivering a finished product.

To achieve this task automatically, the computer needs to learn by example: it needs to see a relevant sample of the wing images in which landmark positions have been located manually. From this, it will learn and reproduce the task automatically. This means that someone had to manually click the landmark position on a few wing images.

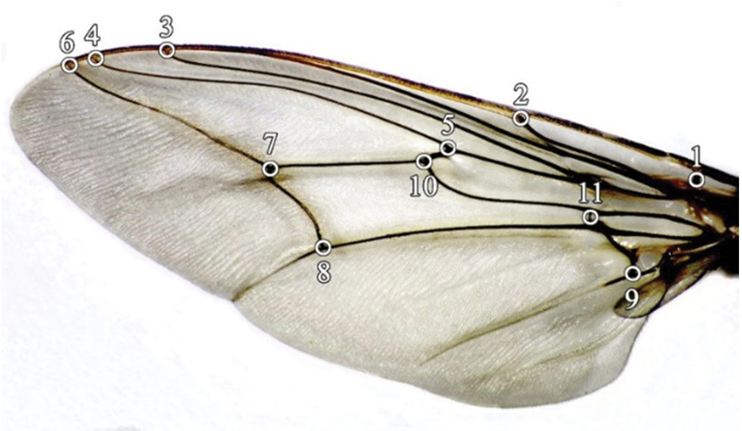

Photo: Dr Lee Haines (reproduced with permission)

Figure 1: The wing of a tsetse, showing the 11 landmarks used to characterise its size and shape.

This is when Prof. Willie Brink from Applied Mathematics stepped up and located the 11 landmarks on approximately 2500 images. This tedious and time-consuming task (approximately one week's work) is crucial to reap the benefits of the artificial intelligence that can then perform the same task on a 10-fold larger data set in a matter of minutes.

However, the training of the machine is also not a trivial task. In essence, it needs to be given an image as input and return as output the two Cartesian (*x*,*y*) coordinates of the 11 landmarks (i.e. a list of 22 numbers). This is essentially a very complex and non-linear function that maps a large list of numbers representing the light intensity in each pixel of the image (approximately 50 000) to 22 numbers representing the location of the 11 landmarks on the wing. The machine had to learn this very complicated function from the training set of images that were manually labelled with the 11 landmarks. One of the many possible ways to express such a function is to use a neural network, i.e. a very flexible model that mimics what happens in our brain when we perform the same task on an image. The light intensity gets sensed through our eyes and the information is communicated and processed through a network of neurones until we manage to simplify the whole image into the few relevant locations of interest where the veins of the wing intersect. Similarly, the computer uses a network of nodes (akin to neurones) arranged in layers, where each node in a layer communicates through a weight parameter and a non-linear transformation to the nodes in the preceding and subsequent layers. All these connections between the layers in the neural network perform mathematical operations and transform information as it flows from the input layer (light intensity in each pixel of the wing image) to the output layer (the 22 numbers representing the Cartesian (*x*,*y*) coordinates of the 11 landmarks). Using the training set of the manually labelled images (for which the landmark coordinates are known), the computer learns the appropriate weights connecting the neurones in its network that give the best fit between the input image and the output landmark coordinates. Once this is done, the computer is able to see a new image (one on which it was not trained) and output the coordinates of its 11 landmarks.

This is just one part of the story: the number of layers in the neural networks, the number of neurones in each layer, the specific way in which each layer relates to the adjacent layers, are all decisions that have to be optimised or fine-tuned by the scientists. The whole process involved disparate fields within computer science and applied mathematics, e.g. image processing, computer vision, programming/coding, statistics, machine learning and artificial intelligence.

Next steps

Having developed the methodology, Geldenhuys used his algorithms to produce Cartesian (*x*,*y*) coordinates for >14 000 pairs of wings; the following year, another honours student in Applied Mathematics, Nuhr Ryklief, successfully used his program to increase the total to >21 000 pairs of wings. These wings were all from flies sampled between November 1994 and February 1997 and thus covered all seasons over more than two full years.

The impressive strides made by the two students are only the first steps in developing a fascinating story. What awaits future students is the task of translating the coordinates into measures of shape and seeing how, or indeed if, shape changes with season and various meteorological variables such as temperature and humidity. Aside from answering the initial question about natural variation of shape with season, it is no surprise that we are very interested to see whether it is possible to detect any effect on wing shape of the undoubted changes in climate over recent decades. Dramatic increases in temperature observed at Rekomitjie have already been identified as responsible for a dramatic collapse in populations of *G. pallidipes* at Rekomitjie.[6]

Provenance of the wings

Readers might, by this stage, already have asked themselves why on earth anybody would want to make a collection of >200000 pairs of tsetse wings. The wings were collected as part of a study that was not designed with any intention of investigating wing shape. Instead, the aim was to estimate mortality rates of adult tsetse via the age structure of the adult female population. Tsetse have a unique reproductive cycle involving the production, at 10-day intervals, of a single larva – which can weigh more than its postpartum mother (Figure 2).

Allied to this process is a much-reduced reproductive tract involving cyclical ovulation from paired ovaries of an egg into the uterus. Radical hysterectomy of a female fly allows the measurement of the contents of her uterus and ovaries and a determination of the number of times she has ovulated. This information can then be used to fix – with an accuracy of <3 days – the chronological age of the fly. These estimates were further informed by measurements of the degree to which the trailing edges of a fly's wings are frayed[7] (Figure 3). The field study also involved the measurement of wing length. Both wing fray and, particularly, length were seen to show well-marked seasonal cycles[8,9] (Figure 4).

Photo: Daniel Hargrove (reproduced with permission)

Figure 2: A female tsetse depositing a larva.

The wing collection was thus a central part of the original study and provided crucial information about the relationship between fly size, age, mortality and how these variables were related to each other, and to short-term seasonal changes and longer changes in meteorological variables. But it was only a decade later that it was made clear to us, by James Patterson[5], that there was a lot more important information "written on the wings" – and the collection of the wings, serendipitously, enabled the Geldenhuys study. What this story underlines is the point that a well-designed, carefully conducted study will very often provide important opportunities to use the data for multiple purposes, often not envisaged when the study was initiated.

Some decades prior to the field study, Hargrove was himself a student embarking on a thesis – studying the physics and physiology of flight in tsetse – and thus particularly interested in flies' wings. Both sexes of tsetse feed only on blood, and take blood meals that can, temporarily, increase their body weight by up to a factor of four[10] – and females can have in utero a full-term larva that weighs more than she does. Accordingly, flies need a powerful flight motor, involving thoracic musculature that is proportionately much bigger than that for other insects, and long wings that flap at more than 200 cycles per second.[11,12] The reliance on blood also means that, unusually for a dipteran, tsetse use an amino acid, proline, rather than carbohydrates, to fuel the flight motor.[13]

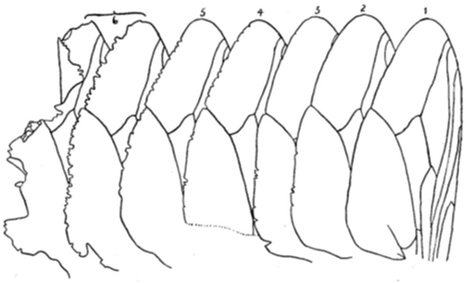

Image: Reproduced with permission from the Bulletin of Entomological Research

Figure 3: Jackson's (1946) categorisation of wing fray in male *Glossina morsitans* Westwood.

As with Darwin's butterflies, evolution is also written on the wings of tsetse – and, as we have seen, much more is written there besides. The study of flight and wings involves delving into physiology, biochemistry, aerodynamics, life history dynamics and variations in meteorological variables, both seasonal and in the longer term. And, of course, we now see that there is both need and ample scope, in studying wing morphometrics, for using mathematical and statistical analyses, computer science and artificial intelligence.

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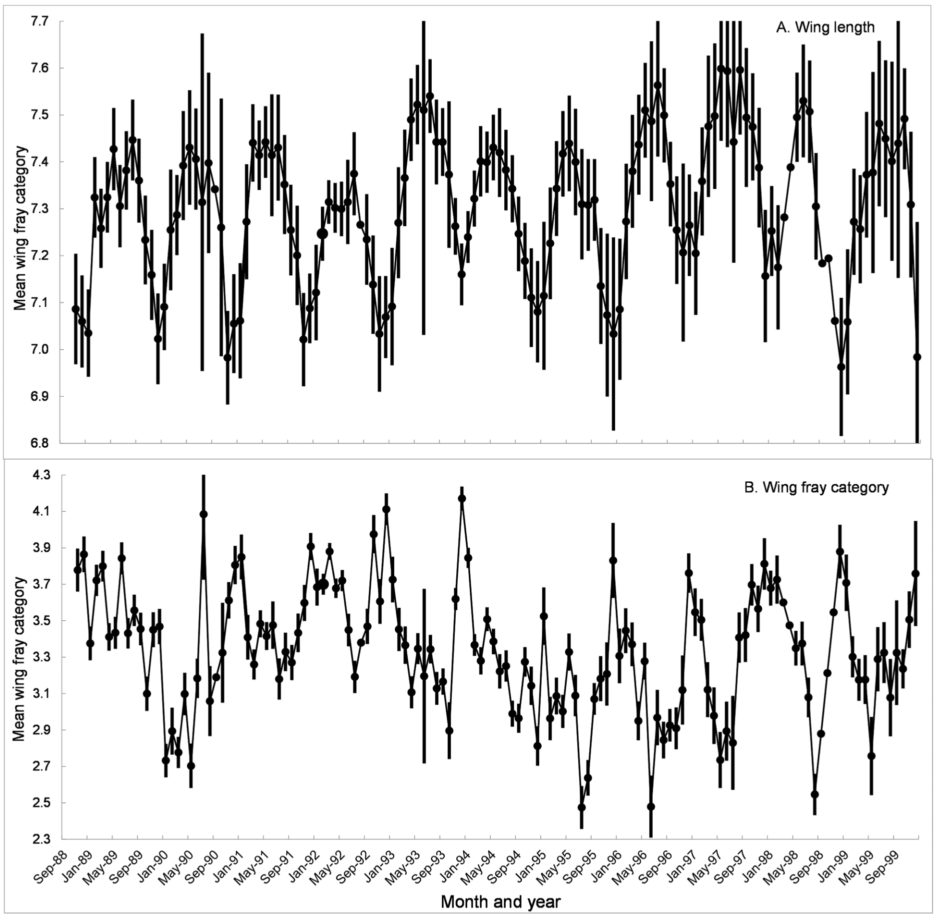
Declarations

We have no competing interests to declare. We have no AI or LLM use to declare. All authors read and approved the final version.



Sources: Based on data from Hargrove[8] and Hargrove et al.[9]

Figure 4: Monthly mean values of (A) wing length and (B) wing fray of female *Glossina pallidipes*, sampled at Rekomitjie Research Station, Zambezi Valley, Zimbabwe, between September 1988 and December 1999.

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